



The association of mineral element concentrations and dietary habits with the risk of cardiovascular diseases: A random forest analysis

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Keywords	Abstract
Cardiovascular diseases Mineral elements Vanadium Dietary habits Random forest Logistic regression	Background and Objectives: Cardiovascular diseases (CVDs) are a major cause of death worldwide, with environmental and dietary factors significantly contributing to the development of these diseases. This study aims to examine how mineral element concentrations and dietary habits together affect CVDs risk. We used a random forest model (RFM) to identify the most predictive factors associated with this risk. Methods: We conducted a cross sectional study of 224 participants, including 102 patients with CVDs and 122 healthy controls aged 35 to 65 years from western Iran. Serum concentrations of 11 mineral elements (aluminum (Al), boron (B), calcium (Ca), cobalt (Co), potassium (K), lithium (Li), magnesium (Mg), manganese (Mn), molybdenum (Mo), phosphorus (P), and vanadium (V)) were measured using Inductively Coupled Plasma Mass Spectrometry (ICP-MS). Dietary habits were assessed through validated questionnaires. Random forest analysis was employed to rank variable importance, followed by logistic regression to evaluate significant predictors of CVDs. Results: The RFM demonstrated high predictive performance, with V, Li, Al, Mn, and Co emerging as the most influential mineral elements. In multivariable logistic regression analysis, higher serum V concentrations were significantly associated with CVDs (Odds ratio (OR) = 8.80, 95% CI: 5.069–15.252), whereas the association between Li and CVDs was not statistically significant based on the reported confidence interval (OR = 3.32, 95% CI: 0.431–25.467). Older age was also associated with higher odds of CVDs (OR = 1.20 per year). Among dietary factors, daily consumption of grilled foods (OR=6.435) and use of solid oil (OR=1.963) were associated with elevated risk. The RFM achieved 97% sensitivity and 100% specificity for mineral elements. Conclusion: Serum V concentrations and selected dietary practices, particularly frequent consumption of grilled foods and use of solid oils, were associated with CVDs. These findings highlight the importance of monitoring mineral element levels and promoting healthier dietary patterns for CVDs prevention.

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Highlights

- Serum vanadium (OR = 8.80) and lithium (OR = 3.32) significantly elevate CVD risk.
- Random forest model shows 97% sensitivity and 100% specificity for CVD prediction.
- Daily grilled food consumption increases CVD odds 6.4 times versus monthly intake.
- Using solid oil for cooking doubles CVD risk compared to liquid oil (OR = 1.96).

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Introduction

Trace elements are minerals present in the body in small amounts that are essential for various physiological functions, including enzyme activity, oxygen transport, and cellular metabolism. However, excessive exposure to certain trace elements can induce oxidative stress and contribute to disease development [1]. Trace elements generate reactive oxygen species (ROS), which can damage proteins, lipids, and nucleic acids in cardiovascular tissues. This oxidative imbalance not only impairs antioxidant defenses but also disrupts vascular endothelial function and exacerbates chronic inflammation [1, 2]. Moreover, mineral elements interfere with lipid metabolism, disturb ion homeostasis, and induce epigenetic changes, all of which contribute to the development of conditions such as atherosclerosis, hypertension, and arrhythmias [3]. For instance, V can interfere with phosphate metabolism and ATPase activity, while Li may disrupt sodium-potassium homeostasis and neurotransmitter signaling, and Al can compete with magnesium and iron in essential enzymatic reactions, collectively contributing to oxidative stress and cardiovascular dysfunction [4-6].

In addition to environmental exposures, dietary patterns are fundamental determinants of cardiovascular health [7]. The shift from nutrient-based to pattern-based research has enhanced our understanding of how the complex interactions of foods and nutrients influence disease risk [8]. Strong and consistent evidence indicates that adopting a healthy dietary pattern which emphasizes high intakes of fruits, vegetables, whole grains, nuts, legumes, unsaturated oils, low-fat dairy, poultry, and fish, while minimizing red and processed meats, high-fat dairy, and sugar-sweetened foods significantly lowers the risk of both fatal and nonfatal CVDs, including

coronary heart disease and stroke [9]. The cardioprotective effects of these dietary patterns are multifactorial. Diets rich in plant-based foods provide a wide array of essential micronutrients, fiber, and antioxidants, which collectively work to lower blood pressure, improve lipid profiles, reduce inflammation, and enhance vascular function [10]. Conversely, diets high in saturated fat, cholesterol, sodium, and added sugars are linked to increased risks of atherogenesis, hypertension, and metabolic dysregulation [11, 12]. Previous studies have looked at the individual links between mineral elements or dietary patterns and CVDs. However, few have used machine learning techniques to rank the relative importance of both categories of exposure simultaneously. Additionally, no such research has been conducted within the Kurdish population of western Iran. Utilizing RFMs presents a valuable opportunity to identify the most influential predictors while considering complex, non-linear relationships that traditional regression methods may overlook. Hence, this study aimed to explore the prospective associations between baseline serum element concentrations and dietary habits with the occurrence of CVDs, as well as to determine the relative importance of these factors using an RFM.

Materials and Methods

Study population

This cross-sectional study was conducted from December 2025 to March 2026 in western Iran among a Kurdish population. For more information, see references [13, 14]. We selected participants using simple random sampling from eligible individuals aged 35–65 years. To qualify, participants had to be within the age range, reside in the region for at least two years, and be Iranian nationals. We excluded individuals with mental

disorders, chronic kidney and liver diseases, cancer, exposure to selected trace elements and minerals, and those who had lived in the area for less than two years. The control group was selected to match the CVDs group's demographic profile. Written informed consent was obtained from all participants, and our study received approval from Kermanshah University of Medical Sciences (ethics number: IR.KUMS.MED.REC.1404.172). We assessed dietary habits using questionnaires and direct interviews with participants; they also provided a three-milliliter fasting blood sample after eight hours of fasting for serum processing. This approach aims to deepen our understanding of the relationship between lifestyle factors and cardiovascular health, contributing essential insights to the field. Dietary habits were assessed using validated semi-quantitative food frequency questionnaires (FFQs) and direct interviews. The FFQ had been previously validated for the Iranian Kurdish population in the Ravansar Non-Communicable Diseases Cohort (RaNCDC) cohort study [13, 14].

Element analysis

To accurately assess mineral element concentrations in blood serum, we used a precise method involving a 2:1 mixture of nitric acid and perchloric acid. One mL of serum was combined with four times its volume of high-purity nitric acid (HNO_3 , 65%, Suprapur, Merck, Germany) and left undisturbed under a chemical hood for 24 hours to facilitate digestion. The next day, we added two mL of perchloric acid (HClO_4 , 70%, Merck, Germany) and heated the mixture in a Bain-Marie (TW12, Julabo GmbH, Germany) at 98 °C for six hours until a clear white solution was obtained. After cooling, we filtered the samples and brought the volume to 25 mL with deionized water (18.2 M Ω -cm at 25 °C, Fiestreem, WSC044, UK). Using Inductively Coupled Plasma Mass Spectrometry (ICP-MS, Agilent 7900, Santa Clara, CA, USA), we measured levels of Al, B, Ca, Co, K, Li, Mg, Mn, Mo, P, and V. The recovery rates for these elements ranged from 92% to 105%, confirming the method's reliability.

Five analyses were performed for both spiked fractions and control samples. ICP-MS operational parameters included a radiofrequency power of 1.5 kW, a plasma gas flow rate of 15 L/min, and a detection mode set to auto. Results were reported in micrograms per liter ($\mu\text{g/L}$) of serum, providing robust insight into mineral element levels.

Statistical analysis

In this study, we first assessed the normality of quantitative variables using the Kolmogorov-Smirnov test. Normally distributed variables are reported as mean $\pm$ standard deviation (SD); non-normally distributed variables are reported as median and interquartile range (IQR). Qualitative variables were described in terms of frequency and frequency percentage. To compare quantitative variables between the control and CVDs groups, we employed the Student's t-test for normally distributed data. For non-normally distributed data, we utilized the Mann-Whitney test. Additionally, we compared the percentages of qualitative variables between the groups using the chi-square test. To evaluate the impact of demographic characteristics, mineral element concentrations, and dietary habits on the CVDs status, we employed logistic regression. Due to the relatively large number of studied characteristics (29 variables) compared to the number of observations (224), the logistic regression model faced challenges related to overfitting. To address this, we first applied a random forest analysis to identify the most significant variables, separating mineral element concentrations from dietary habits. We then fitted the logistic regression model using only these key variables. Moreover, since the distribution of heavy metal concentration variables was right-skewed, we applied a log₂ transformation within the logistic regression model.

RFM is a machine learning classifier that uses multiple decision trees to predict classifications, such as CVDs or control, based on majority voting from the trees. The process for constructing an RFM involves: 1. Dividing the dataset into training and test sets. 2. Randomly selecting a

bootstrap sample from the training set. 3. Randomly choosing a subset of explanatory variables. 4. Building a decision tree by selecting the best variable at each node until the maximum tree size is reached. This continues until a specified number of trees, often 500, are created (15). Variable importance is assessed using the Mean Decrease Gini Index, with higher values indicating greater significance in predicting outcomes [16]. In this study, RFM was used to identify key variables affecting CVDs, which were then included in a multiple logistic regression model. The data was split 70:30 for training and testing, with performance evaluated on accuracy, sensitivity, and specificity. The "randomForest" package was used for model fitting and the "caret" package for evaluation in R software [17, 18]. All statistical tests were conducted in R software (version 4.0.3; R Foundation for Statistical Computing, Vienna, Austria), with a significance level set at 0.05.

Results

A total of 224 subjects were examined, consisting of 122 individuals (54.5%) in the control group and 102 individuals (45.5%) in the CVDs group. The mean age of the CVDs patients was 52.68 years (± 8.26), which was significantly higher than the mean age of the control group at 45.61 years (± 7.81) ($p < 0.001$). Table 1 presents the concentrations of mineral elements in both the control and CVDs groups. Serum concentrations of Al, B, Co, K, Li, Mn, Mo, P, and V were significantly higher among participants with CVDs than among controls (all $p < 0.001$). Although the mean Mg concentration was slightly higher in the CVDs group, this difference was not statistically significant (13.30 ± 7.9813 vs. 12.40 ± 10.10 , $p = 0.348$). Similarly, Ca concentrations did not differ significantly between the groups (89.90 ± 49.50 vs. 97.29 ± 29.25 , $p = 0.067$). Additionally, the comparative analysis of dietary habits between individuals with CVDs and a control group showed no statistically significant differences across all measured variables ($p > 0.05$; Table 2).

Both groups exhibited similar patterns in their frequency of consuming grilled, fried, and smoked foods, as well as in their preferences for frying vegetables, potatoes, and onions. The use of cooking oils, salt practices, and behaviors such as reusing oil or using scratched Teflon cookware was also comparable. These findings suggest that dietary behaviors were largely consistent between the two groups, indicating that eating habits alone may not explain the differences in cardiovascular health status.

Table 1 Concentrations of mineral elements by control and CVDs groups

Mineral elements*	Group		p-value
	Control (n=122)	CVDs (n=102)	
Al ($\mu\text{g/L}$)	2.10 $\pm$ 2.20	15.55 $\pm$ 7.53	<0.001**
B ($\mu\text{g/L}$)	80.00 $\pm$ 50.00	110.10 $\pm$ 79.60	<0.001**
Ca ($\mu\text{g/ml}$)	97.29 $\pm$ 29.25	89.90 $\pm$ 49.50	0.067
Co ($\mu\text{g/L}$)	0.086 $\pm$ 0.01	0.50 $\pm$ 0.30	<0.001**
K ($\mu\text{g/ml}$)	127.50 $\pm$ 82.70	179.40 $\pm$ 79.85	<0.001**
Li ($\mu\text{g/L}$)	0.25 $\pm$ 0.17	1.10 $\pm$ 0.80	<0.001**
Mg ($\mu\text{g/ml}$)	12.40 $\pm$ 10.10	13.30 $\pm$ 7.98	0.348
Mn ($\mu\text{g/L}$)	1.90 $\pm$ 1.60	10.25 $\pm$ 4.87	<0.001**
Mo ($\mu\text{g/L}$)	0.30 $\pm$ 0.30	2.90 $\pm$ 3.13	<0.001**
P (mg/dL)	3.17 $\pm$ 2.12	6.82 $\pm$ 5.61	<0.001**
V ($\mu\text{g/L}$)	0.10 $\pm$ 0.10	0.80 $\pm$ 0.40	<0.001**

*Data are presented as mean $\pm$ SD. Abbreviations: CVDs, Cardiovascular diseases; SD, Standard deviation; Al, Aluminum; B, Boron; Ca, Calcium; Co, Cobalt; K, Potassium; Li, Lithium; Mg, Magnesium; Mn, Manganese; Mo, Molybdenum; P, Phosphorus; V, Vanadium. **Significant test in level 0.05.

Table 2 Dietary habits status by control and CVDs groups (n (%))

Eating habits		Control (n=122)	CVDs (n=102)	p-value
Grilled food	0-3 time per month	40(32.8)	32(31.4)	0.722
	1-3 time per week	55(45.1)	51(50.0)	
	Daily	27(22.1)	19(18.6)	
Fried food	0-3 time per month	11(9.0)	5(4.9)	0.467
	1-3 time per week	19(15.6)	15(14.7)	
	Daily	92(75.4)	82(80.4)	
Smoked food	Less than once per month	121(99.2)	98(96.1)	0.160

	1-3 time per month	1(0.8)	1(1.0)	
	1-3 time per week	0(0.0)	3(2.9)	
Potato fry type	Does not fry foods or Sautéing	3(2.5)	5(4.9)	0.580
	until golden yellow	77(63.1)	65(63.7)	
	until browned	42(34.4)	32(31.4)	
Vegetable fry type	Does not fry foods or Sautéing	17(13.9)	10(9.8)	0.514
	until golden yellow	33(27.0)	33(32.4)	
	until browned	72(59.0)	59(57.8)	
Onion fry type	Does not fry foods or Sautéing	7(5.7)	6(5.9)	0.615
	until golden yellow	77(63.1)	58(56.9)	
	until browned	38(31.1)	38(37.3)	
Used oil type	Solid oil (Ghee)	35(28.7)	28(27.5)	0.283
	Semi-solid oil (Margarine)	15(12.3)	14(13.7)	
	Liquid oil	3(2.5)	9(8.8)	
	Frying oil	69(56.6)	51(50.0)	
Salt use at the table	Yes	33(27.0)	31(30.4)	0.853
	Sometimes	38(31.1)	31(30.4)	
	No	51(41.8)	40(39.2)	
Food salt used	Little salt	46(37.7)	34(33.3)	0.744
	Regular	60(49.2)	52(51.0)	
	Salty	16(13.1)	16(15.7)	
Reuse oil	No	84(68.9)	74(72.5)	0.560
	Yes	38(31.1)	28(27.5)	
Reuse mold	No	61.0(50.0)	55(53.9)	0.593
	Yes	61.0(50.0)	47(46.1)	
Used scratched Teflon	No	82(67.2)	62(60.8)	0.330
	Yes	40(32.8)	40(39.2)	

*Significant test in level 0.05

Figure 1 illustrates the relative importance of mineral elements in predicting CVDs, using the mean decrease in the Gini index derived from the RFM. Among the evaluated elements, Li, Al, Mn, Co, and V emerged as the most influential predictors. The RFM demonstrated high classification performance for these variables, achieving sensitivity, specificity, and accuracy

values of 0.97, 1.00, and 0.985, respectively. These findings highlight the potential role of specific heavy metal concentrations as biomarkers in assessing CVDs risk. Figure 2 presents the importance ranking of dietary habit variables in predicting CVDs, also based on the mean decrease in the Gini index from the RFM model. The most impactful factors identified were the type of grilled food consumed, the type of oil used in cooking, and the use of salt at the table. Although the predictive power of dietary variables was lower than that of mineral elements, the RFM model still showed reasonable performance metrics, with sensitivity, specificity, and accuracy values of 0.89, 0.75, and 0.71, respectively. These results suggest that while dietary habits contribute to CVDs risk, their predictive strength may be more modest compared to biochemical markers.

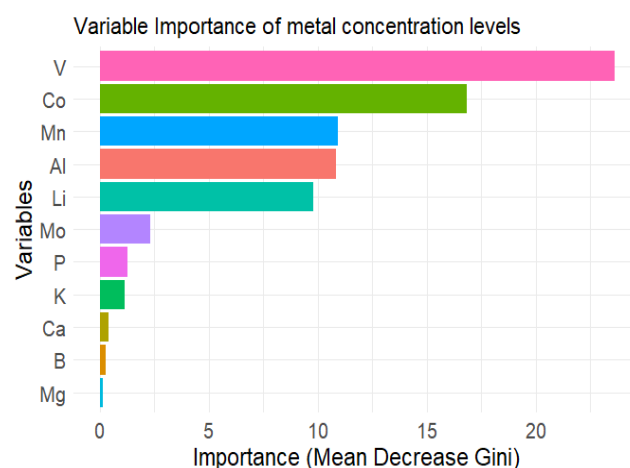


Fig. 1 Variable importance ranking of mineral elements in predicting CVDs based on the mean decrease in Gini index from the RFM. Higher Gini values indicate greater predictive importance.

The findings from the logistic regression model, which incorporated the most significant variables identified through random forest analysis (see Figures 1 and 2), are summarized in Table 3. The results indicate that with each additional year of age, the likelihood of developing CVDs increases by 1.2 times (OR=1.2; 95% CI: 1.03, 1.399). Furthermore, higher levels of Log2 (V) significantly elevate the risk of CVDs, with an OR of 8.80 (95% CI: 5.069, 15.252). Similarly, Log2 (AL) is associated with

an increased risk, showing an OR of 3.77 (95% CI: 1.814, 7.830).

Furthermore, the logistic regression analysis demonstrated that individuals who consumed grilled food 1–3 times per week had approximately four-fold higher odds of CVD compared with those who consumed grilled food 0–3 times per month (OR = 4.411; 95% CI: 3.015–6.451). The odds of CVD were approximately six-fold higher among individuals who consumed grilled food daily (OR = 6.435; 95% CI: 1.89–21.803).

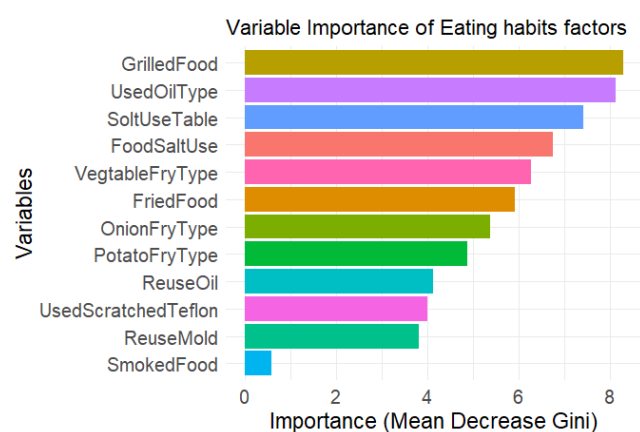


Fig. 2 The order of importance of eating habits factors in predicting CVDs based on the mean decrease in Gini index.

Table 3 Result of logistic regression for affecting important factors on CVDs*

Estimation of coefficients				
Variables	Estimate (SE)	P-value	OR	95% CI
(Intercept)	-	0.255	-	-
Age	6.411(5.634)			
	0.183 (0.078)	0.019*	1.201	(1.030, 1.399)
Log2 (V)	2.174 (0.281)	< 0.0001*	8.80	(5.069, 15.252)
Log2 (Co)	-0.284 (0.207)	0.170	0.752	(0.501, 1.129)
Log2 (Mn)	-0.350 (0.453)	0.440	0.704	(0.289, 1.712)
Log2 (Al)	1.327 (0.373)	< 0.001*	3.77	(1.814, 7.830)
Log2 (Li)	1.199 (1.040)	0.249	3.32	(0.431, 25.467)
Grilled food (0-3 time per month as reference)				
1-3 time per week	1.484(0.194)	<0.001*	4.411	(3.015, 6.451)
Daily	1.861(0.623)	0.003*	6.435	(1.89, 21.803)
Used oil type (Liquid oil as reference)				
Solid oil (Ghee)	0.674(0.408)	0.098	1.963	(0.881, 4.365)

Semi-solid oil (Margarine)	-	0.336	0.131	(0.002, 8.228)
Frying oil	2.026(2.109)	-	0.314	0.424 (0.080, 2.247)
Salt use at the table (No)	0.856(0.850)	-	-	-
Sometimes	-	0.403	0.280	(0.014, 5.427)
Yes	1.270(1.511)	-	0.400	0.322 (0.022, 4.589)
	1.132(1.355)	-	-	-

*Abbreviations: CVDs, Cardiovascular diseases; OR, Odds ratio; CI, confidence interval, SE: standard error; Al, Aluminum; Co, Cobalt; Li, Lithium; Mn, Manganese; V, Vanadium. *Significant at 0.05

Discussion

This study aimed to investigate the importance of mineral elements in predicting CVDs, using the RFM. The Gini index derived from the RFM showed that, among the evaluated elements, V emerged as the most influential predictor. Also, the findings from the logistic regression model, which incorporated the most significant variables identified through random forest analysis, indicate that higher levels of V significantly elevate the risk of CVDs, with an OR of 8.80 (95% CI: 5.069, 15.252). Most V compounds come mainly from the fossil fuel combustion of vehicles and marine vessels. The general population is exposed to V via the respiratory route in ambient air. High V concentrations have been found in occupational settings, particularly in boiler cleaning due to the presence of V oxides in the dust. Boiler repair work in power plants is linked to occupational exposure to V compounds and other complex mixtures of toxic agents [19]. Vanadium exists in respiratory ambient particulates in an easily soluble form, which makes it bioavailable through inhalation and is thought to contribute to the development of adverse health problems [20].

Vanadium is an essential substance to support biological activities, but it also can cause organ injury when its concentration exceeds the body's tolerance. Because cardiomyocytes have a high energy demand and a high mitochondrial density, the heart may be particularly vulnerable to mitochondrial damage induced by vanadium exposure [21]. Some studies demonstrated that excessive V could cause the injury of cardiac tissues via promoting the generation of ROS and impaired antioxidant defense systems, [22–24], which in turn may contribute to oxidative stress

and mitochondrial dysfunction by complex signaling mechanisms.

Epidemiological studies on vanadium in general populations are scarce. Li et al. [25] in a cross-sectional study on two groups of workers selected from a vanadium plant (vanadium group) and a cold-rolling mill (control group), found that Vanadium compounds pose potential risks to the cardiovascular health of workers exposed to vanadium. It is worth considering that there are adverse health outcomes identified from epidemiological studies for associations between vanadium exposure and CVDs mortality or all-cause mortality [19]. Our finding that vanadium was the strongest predictor of CVDs (OR = 8.80) is consistent with previous epidemiological studies. The Six California Counties Study adds to the growing body of evidence linking variation of specific PM_{2.5} components with excess risks of mortality. The study showed that almost all of the pollutants (including PM_{2.5}, EC, OC, SO₄, Cu, Fe, Mn, V and Zn) were associated with all-cause and cardiovascular mortality except for Al, Br, and Ni during the cooler months [26]. Tian et al, [27] examined the association between the levels of PM_{2.5} chemical components and CVDs mortalities in Hong Kong. They found statistically significant evidence that CVDs mortalities were higher in days with higher concentrations of V (ER 4.7%; 95% CI: 1.5%–8.0%), Ni (ER = 4.1%; 95% CI: 1.1%–7.1%), and organic carbon (ER = 0.8%; 95% CI: 0.2%–1.4%). The primary outcomes were cross-sectional measurements in 2005-2007 of seated systolic and diastolic blood pressure from 5517 participants aged 45-84 in the Multi-Ethnic Study of Atherosclerosis (MESA). These results indicate that exposure to vanadium may be associated with increases in both SBP and DBP [28]. Additionally, our study population from western Iran may have different baseline exposure levels and susceptibility profiles compared to the US and Hong Kong populations.

The increased cardiovascular risks linked to high serum V, along with regular consumption of grilled foods and solid cooking oils, highlight a pressing health concern. These risks arise from interconnected pathways of oxidative stress,

mitochondrial dysfunction, and metabolic disruption that affect heart health. Vanadium compounds, particularly in their +4-oxidation state, are potent pro-oxidants that significantly impair cardiac mitochondrial function, disrupting respiration and inducing swelling through the mitochondrial calcium uniporter [11]. Additionally, cooking meats at high temperatures produces harmful substances like polycyclic aromatic hydrocarbons (PAHs) and heterocyclic amines, which can elevate oxidative stress, inflammation, and blood pressure [9, 12]. Solid cooking oils, high in saturated fats, further contribute to dyslipidemia by raising LDL cholesterol and promoting systemic inflammation [7, 10]. Collectively, the interplay between mineral element toxicity, dietary oxidative burdens, and lipid imbalances may compromise endogenous antioxidant defenses, thereby contributing to an elevated cardiovascular risk. Recognizing these risks is vital for making heart-healthy dietary choices. However, further studies are needed to understand their health effects better.

Limitations

This study has several limitations that should be considered when interpreting its findings. First and foremost, the cross-sectional design prevents us from establishing causal relationships between mineral element concentrations, dietary habits, and CVDs risk. While we observed strong associations, particularly for vanadium and lithium, we cannot determine whether elevated levels of these elements precede the development of CVDs or are influenced by the disease itself. A longitudinal study with repeated measurements is essential to clarify the temporal sequence and better assess the long-term health effects of chronic exposure to both ambient and dietary sources of these elements. Second, our sample size of 224 participants was relatively small, which may have limited the statistical power for detecting subtle associations, especially in subgroup analyses. The wide confidence intervals observed for some ORs (e.g., lithium: 95% CI: 0.431–25.467) reflect this limitation and indicate

that the precision of our estimates could be improved with a larger cohort. Third, although we measured serum concentrations of mineral elements, these levels reflect recent exposure rather than the cumulative long-term body burden. Additionally, dietary habits were assessed through self-reported questionnaires, which are subject to recall bias and social desirability bias, potentially leading to misclassification of exposure. Lastly, our study population was exclusively drawn from the Kurdish community in western Iran, which may limit the generalizability of our findings to other ethnic groups and geographic regions with different environmental exposures and dietary patterns. Future studies should address these limitations by using prospective designs, larger and more diverse populations, and more comprehensive methods for assessing exposure.

Conclusion

This study demonstrates that elevated serum levels of V, along with unhealthy dietary habits, are strongly associated with an increased risk of CVDs. Vanadium had the most significant effect (OR = 8.80), followed by lithium (OR = 3.32). Daily consumption of grilled foods (OR = 6.435) and the use of solid oils (OR = 1.963) were also significant dietary risk factors. The RFM showed excellent predictive performance, with a sensitivity of 97% and a specificity of 100%. These findings highlight the importance of monitoring mineral element exposure and promoting healthier dietary patterns for CVDs prevention. However, the cross-sectional design of the study limits the ability to establish causal relationships. Additionally, the modest sample size and reliance on self-reported dietary data present further constraints. Future longitudinal studies with larger and more diverse populations are needed to confirm these associations and inform public health interventions.

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Authors' Contributions

NS and BM generated the idea and design of the study. BM, HJ, RA, and SN searched the literature in databases and wrote parts of the manuscript. ZM participated in statistical analyses and edited the results section. All authors reviewed the manuscript. SN wrote the discussion section and, together with BM, supervised all parts of the revision process. BM served as the corresponding author and oversaw the overall project coordination.

Data availability

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

Conflicts of interest

The authors declare that they have no competing or conflicting interests in conducting this study.

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Ethics approval and consent to participate

The study's protocols were reviewed and approved by Kermanshah University of Medical Sciences' Ethics Committee (Ethics code: IR.KUMS.MED.REC.1404.172). Also, each participating woman reviewed the study protocol and signed a consent form prior to being enrolled in the study.

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